European Journal of Operational Research 269 (2018) 272–285

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/ejor

Promoting sustainability of automotive products through strategic assortment planning

Edward Lawrence Umpfenbach, Evrim Dalkiran*, Ratna Babu Chinnam, Alper Ekrem Murat

Industrial and Systems Engineering, Wayne State University, 4815 Fourth Street, Detroit, MI 48202, United States

ARTICLE INFO

Article history:
Received 31 August 2016
Accepted 17 August 2017
Available online 24 August 2017

Keywords:
OR in environment and climate change
Assortment planning
Automotive products
Network design
Sustainability and environmental regulations

ABSTRACT

Assortment planning seeks to find an optimal set of products that the company should offer to its customers. Traditionally, it is a trade-off between offering larger assortments to maximize customer choice vs. smaller assortments to minimize costs associated with design, manufacturing, and distribution. Existing assortment planning models are quite lacking when it comes to configurable products such as automobiles and detail level of supply chain considerations. Further complications stem from increasingly strict environmental regulations and broader expectations for sustainable products and supply chains. We present a mixed-integer linear programming formulation for integrated assortment and supply chain network design models for automotive products to provide effective decision support and directional guidance to strategic product planners. Our models account for product use and supply chain emissions as well as fuel efficiency requirements. We also present an illustrative case study motivated by a global automaker to demonstrate the utility of the models and study the effects of sustainability requirements on the assortment and supply chain design.

© 2017 Elsevier B.V. All rights reserved.

1. Introduction

Sustainability is becoming an utmost priority for many organizations, governments, and citizenry around the world. While there are several reasons for this trend, the negative effects of global warming in the form of extreme weather events, related illnesses, and economic losses can be readily witnessed all around (Denchak, 2016; Nature.org, 2016). The United Nations (U.N.) concluded that climate change is a global issue, affecting every country, and is expected to affect even more in the future (United Nations, 2016).

The global surface temperature has increased by 1.5 degree Fahrenheit since 1880, with more than half of that rise is observed since 1980 (UCSUSA, 2016). Data show that carbon dioxide (CO_2) levels have steadily increased every year, with levels 25% higher today than in 1957, and has contributed the most to climate change between 1750 and 2005 (Jones et al., 2007). One of the primary contributors to CO_2 emissions is the transportation sector. Globally, transportation is contributing 14% of the greenhouse gas (GHG) emissions (U.S. EPA, 2014). The GHGs, including CO_2, methane, ozone, and the fluorocarbons, absorb solar and thermal radiation as well as heat fluxes from Earth's surface, and in turn the atmosphere warms the Earth's surface which is called as the "greenhouse effect". In 2013, transportation contributed more than half of the carbon monoxide and nitrogen oxides (UCSUSA, 2016) and over a quarter of the total U.S. GHG emissions, only second to the electricity sector (U.S. Department of State, 2014). Of these emissions in the transportation sector, more than half come from gasoline consumption of automobiles and other highway vehicles (U.S. EPA, 2014), and is the focus of this study.

Early on, the "Brundtland Report" commissioned by the U.N. led to the recognition that while the environmental focus of sustainability efforts is important, a balanced concern for also the economic and social pillars of sustainability is also critical (Brundtland et al., 1987). It defined sustainable development as "the development that meets the needs of the present without compromising the ability of future generations to meet their own needs". While disagreements exist today regarding the "three legged-stool" model of sustainable development (Dawe & Ryan, 2003), it is understandable that the private sector has to be concerned about profitability of their products/services besides environmental sustainability. This is certainly the case for the automotive industry with its global and complex supply chains that is expected to produce nearly 90 million vehicles globally in 2016 (Lehle, 2016). The product assortment planning models proposed in this study aim to help strategic product planning groups within the automotive companies to better understand and manage these trade-offs, in particular, the trade-offs between the resulting GHS emissions

* Corresponding author.
E-mail addresses: Eumpfenbach@wayne.edu (E.L. Umpfenbach), evrimd@wayne.edu, evrim.dalkiran@gmail.com (E. Dalkiran), Ratna.Chinnam@wayne.edu (R.B. Chinnam), Amurat@wayne.edu (A.E. Murat).

http://dx.doi.org/10.1016/j.ejor.2017.08.031
0377-2217/© 2017 Elsevier B.V. All rights reserved.

during production and use, and the sales/profitability of the vehicle programs.

We define *assortment* as the set of products a manufacturer builds and offers to its customers. The goal of the *assortment planning* is to identify an assortment that maximizes sales, profit, or gross margin while satisfying numerous constraints including budget, shelf space, and capacity (Kök, Fisher, & Vaidyanathan, 2008). A *configuration* is a combination of required (e.g., powertrain, seats, wheels) and optional (e.g., moonroof, adaptive cruise control) components, and each model is offered in various configurations for *configurable products* (Rodríguez & Aydın, 2011). Taghavi and Chinnam (2014) introduced *product definition* as the set of configurations and the corresponding logic for a configurable product. Assortment planning requires balanced trade-offs between expected sales, revenue, and product offering costs (MacDuffie, Sethuraman, & Fisher, 1996), not to mention environmental impact, which is the focus of this study.

The product offerings and configurations have steadily grown globally in the automotive industry until recent years. For instance, the number of automobile models offered in the U.S. increased from 30 in 1955 to 142 in 1989 (Womack, Jones, & Roos, 1990), and to 394 in 2013 (Baumann, 2013). However, Pil and Holweg (2004) have not found significant correlation between the number of configurations and total sales for European automotive market. In addition, large product configuration assortments come with increased cost due to manufacturing complexity and productivity problems. Recently, the volume-driven original equipment manufacturers (OEMs) have begun to control their assortments to attain a balance between operational costs, sales, and market shares (Taghavi & Chinnam, 2014). This is particularly the case for the North American (NA) market given that vast majority of customers buy or lease vehicles from the dealer's limited on-hand or local inventory (unlike European markets where a majority of the vehicles might be built-to-order). For instance, Ford Motor Company reduced the number orderable configurations by more than 90% for 2009 F-150 and cut the number of core entity combinations by 95% for 2010 Ford Focus, in comparison to prior models (Wilson, 2008). OEMs lack objective and holistic decision support tools for their strategic assortment planning problems for managing product variety, sales, market share, and costs (Kremer et al., 2016; Taghavi & Chinnam, 2014; Umpfenbach, 2013).

In the automotive industry, there are increasingly strict governmental regulations effecting product offerings (Geffen & Rothenberg, 2000; Koplin, Seuring, & Mesterharm, 2007). In the U.S., the Corporate Average Fuel Economy (CAFE) standards are the main federal regulations, which are set by the National Highway Traffic Safety Administration (NHTSA). The achieved CAFE level, expressed in miles per gallon (3.785 liters), is the production-weighted harmonic mean of fuel economy of an OEM's fleet for a given model year. The required CAFE levels are calculated based on the CAFE standards and characteristics of the OEM's fleet. From 1978 to 1984, the CAFE standards significantly increased from 18 miles per gallon to 27 miles per gallon and stayed relatively stable until 2010 for passenger cars. Since 2011, CAFE standards are expressed as a function of vehicle wheelbase and average track wide. The CAFE targets are rapidly increasing over the next several years: For passenger cars and light-duty tracks, the fuel economy target of 35.5 miles per gallon in 2016 will increase to 54.5 miles per gallon in 2025. If an OEM does not achieve the required CAFE levels, the OEM either applies for CAFE credits or pays a penalty, which is currently $5.5 per 0.1 miles per gallon for every vehicle produced for the U.S. market. Additionally, the Gas Guzzler Tax applies to passenger cars with fuel economy less than 22.5 miles per gallon and can reach up to $7700 per vehicle in 2016. Alternatively, some countries, including European states, followed high fuel taxation policy (Ekins, 1999; Sterner, 2007). This policy has been seen one of the most effective instruments for controlling energy consumption and air pollution as well as promoting cleaner fuels and alternative energy sources in transportation sector (Steenberghen & Lopez, 2008).

Overall, product assortment planning models are lacking when it comes to facilitating effective trade-offs between market share, profitability, and broader sustainability considerations (Taghavi & Chinnam, 2014). This is particularly the case for configurable products as is the case within the automotive industry and others (Kremer et al., 2016; Taghavi & Chinnam, 2014; Umpfenbach, 2013). This study aims to address these shortcomings and provides a tractable modeling framework that is particularly aimed at supporting upfront strategic product planning efforts in automotive companies, that often take place several years ahead of actual production. The goal is to provide effective decision support and directional guidance to product assortment planners while accounting for the entire product life-cycle.

Due to differences in fuel-efficiency regulations, customer expectations, and even differences in the fuel and road infrastructure, OEMs often tailor their vehicles to specific market needs. For example, European vehicles tend to be much smaller due to narrow streets in many cities/countries, and lighter due to stricter regulations and higher fuel-efficiency expectations with respect to North American products (Spector, 2007). Hence, European products generally employ more lighter materials (e.g., by replacing steel body panels with aluminum panels) and adopt efficient powertrains (e.g., use smaller engines with turbochargers instead of naturally aspirated engines to provide better fuel efficiency) albeit at the expense of higher product pricing. For this reason, our models are aimed at providing assortment planning guidance and support for product planning groups working on individual products for specific markets (e.g., the mid-size (C-segment) Ford Focus car for North America). To the best of our knowledge, this is the first study aimed at strategic product assortment planning for configurable products with integrated consideration for supply network design, manufacturing, logistics, supply chain carbon footprint, and product use emissions considerations. While the study is mainly aimed at the automotive industry, the proposed models can be adapted to other industries and sectors that deal with configurable products (e.g., copiers, computers, housing appliances).

The main contributions of this paper are as follows. First, we introduce sustainability aspect to the integrated assortment planning and supply chain optimization problem. Second, we utilize three variants of sustainability targets for an automaker: average fuel efficiency of a fleet, average product use CO_2 emissions, and average supply chain CO_2 emissions. Third, a case study based on a North American automotive manufacturer is introduced with extensive parameter estimation via consultation with subject matter experts. Fourth, we discuss the effects of each sustainability target on profit, sales, average fuel efficiency, as well as product use and supply chain CO_2 emissions.

The remainder of this paper is organized as follows. Section 2 discusses the related literature. The strategic assortment planning problem and constraints pertaining to sustainability targets are introduced in Section 3. Section 4 discusses data considerations for sustainability modeling. Section 5 analyzes the effects of sustainability constraints on the assortment and supply chain design via a case study. Finally, Section 6 concludes the paper with a summary and recommendations for future research.

2. Literature review

Our contribution relates to the literature on assortment planning, effect of environmental emissions and standards on automotive manufacturing, life-cycle analysis of automotive products

and integration of sustainability in supply chain operations of automotive manufacturers.

Product variety and product line design (PLD) is one of the main branches of assortment planning literature (Kök, Fisher, & Vaidyanathan, 2008). One of the first models on product variety is introduced by Hotelling (1929), in which the locations of single product firms on a line segment and their prices are determined to maximize the profit from uniformly distributed customers. Extensions of Hotelling model incorporate horizontal and vertical product differentiation (see Anderson, De Palma, & Thisse, 1992). Mussa and Rosen (1978) and Moorthy (1984) introduced PLD problem, which is to choose a subset of products among vertically differentiated products and to set their prices for maximizing profit. Several extensions of PLD are studied, including joint marketing and production decisions (Eliashberg & Steinberg, 1993; Michalek, Ceryan, Papalambros, & Koren, 2006), component commonality (Desai, Kekre, Radhakrishnan, & Srinivasan, 2001; Heese & Swaminathan, 2006), inventory considerations (Chen, Eliashberg, & Zipkin, 1998; Netessine & Taylor, 2007), and fixed costs for selected products (Dobson & Kalish, 1993). Our assortment planning model significantly extends PLD problem by incorporating component commonality, design integration, manufacturing, and supply chain complexities.

Research on assortment planning with integrated supply chain considerations is still in its infancy. Van Ryzin and Mahajan (1999) is the first to study assortment planning and inventory decisions where the consumer choice is modeled using a multinomial logit (MNL) model. In their study, the variety trade-off in assortment planning is investigated under identical prices and costs in a newsvendor setting. Smith and Agrawal (2000) studied inventory management and assortment planning problem with exogenous demand model. Mahajan and Van Ryzin (2001) analyzed a newsvendor model, where customers dynamically substitute product variants under stockout. The numerical examples demonstrate that under dynamic substitution, popular variants should be stocked more than the traditional newsvendor model suggests. Kök and Fisher (2007) also studied assortment optimization problem under stockout and assortment-based substitution, where they proposed a procedure for estimating the substitution parameters and iterative optimization heuristic for solving the problem. The proposed method resulted in a more than 50% profit increase in the context of a supermarket chain. Honhon, Gaur, and Seshadri (2010) developed a dynamic programming algorithm and proposed a heuristic for the assortment planning problem under the stockout-based substitution. These assortment planning studies do not consider sustainability and environmental impact, and manufacturing and supply chain integration is limited. More recently, Taghavi and Chinnam (2014) proposed a mixed-integer programming framework to account for economic and environmental requirements during product assortment planning but with a focus on powertrain technology selection.

In terms of emissions and standards perspective, Goldberg (1998) assessed the effects of CAFE regulations on automobile prices, sales, and fuel consumption via simulations. MacLean and Lave (2000) estimated energy use, GHG and pollutant emissions of alternative fuel-powertrain options including compressed natural gas (CNG) and alcohols. It is found that CNG vehicles have the best emission performance, whereas direct injected diesel engines have the worst and may not satisfy the emission standards without lowering the efficiency. The effects of fuel efficiency and emission policies, such as CAFE standards, CO_2 emission taxes, and diesel technology quotas, on vehicle design in an oligopoly market are studied utilizing game theory in Michalek, Papalambros, and Skerlos (2004). Their results demonstrate that CO_2 taxes generate diminishing returns on fuel efficiency and may not be sufficient to incentivize producers to introduce alternative fuel vehicles, whereas CAFE standards attain higher fuel efficiency per regulatory dollar and reduce the cost of consumers and producers as a result of competition. Hoen, Tan, Fransoo, and Van Houtum (2010) studied regulations based on emission cost and emission constraint for transport mode selection in supply chains. Their results show that emission cost is not sufficient enough to change transport modes, whereas restrictions on freight transport emissions can result in large reductions in carbon emissions. We have also studied the effect of average emission restriction for the product use and supply chain rather than emission cost.

Many researchers have focused on life-cycle analysis (LCA) of automobiles and technologies. Graedel, Allenby, and Comrie (1995) present a scoring method of LCA to compare the environmental effects of automobiles from cradle-to-grave in the 1950s and 1990s at a very high level. There are several studies focusing on alternative powertrain technologies. For example, Notter et al. (2010) conduct LCA on the environmental impact of lithium ion battery powered vehicles. They find that the environmental impacts of the vehicle operation phase dominate the impacts during production, with operation impacts of electric vehicles (EVs) being heavily dependent on the source of fuel used in producing the electricity. They find the greatest environmental burden from the production of batteries comes from the production of copper and aluminum, used in battery itself and connecting wires. Samaras and Meisterling (2008) study the GHG emissions of plug-in hybrid electric vehicles (PHEVs) and find a 32% decrease in life-cycle GHG emissions compared to a traditional gasoline engine, but small improvements over a traditional hybrid. Also, they report that 2–5% of life-cycle emissions for a plug-in hybrid can be attributed to battery manufacturing. Ma, Balthasar, Tait, Riera-Palou, and Harrison (2012) conduct a life-cycle comparison of EVs and conventional vehicles under different conditions, accounting for factors such as driving behavior and electrical grid load. They find that due to the mixes of fuel sources used at varying electrical grid loads, EVs have lower life-cycle emissions when batteries are charged at times when electrical demand is lowest. Also, EVs perform best compared to conventional vehicles when driven at low speeds, with low weights, and low demands for auxiliary power (such as air conditioning).

Several studies have also been conducted to explore how automotive companies can integrate sustainable production requirements into their daily procedures. Koplin et al. (2007) expose the process followed by one leading OEM, Volkswagen AG, to incorporate sustainable dimensions into its supply chain practices. Taylor (2006) and Khan (2008) illustrate several cleaner production strategies which can be adopted by automotive firms. For an extensive review of this stream of literature, see Pallaro, Subramanian, Abdulrahman, and Liu (2015). Different from this stream of operations literature, we focus on strategic product planning processes with an aggregate life-cycle focus for promoting sustainability of configurable products.

3. Strategic assortment planning problem and sustainability considerations

The mixed-integer fractional programming formulation for the general strategic assortment planning problem is presented in (1)–(13) (Umpfenbach, 2013). The model assists a decision-maker to maximize profit by optimizing the assortment of configurable products to offer to its customers and the supply chain network to manufacture these products. Without loss of generality, the supply chain is assumed to be centralized with two levels of facility decisions, where components are shipped from suppliers to assembly plants, assembled into products, and then finished products are shipped to demand regions. The sets, parameters, and variables utilized in the model are displayed in Table 1. The

Table 1
Sets, parameters, and variables in the integrated assortment and supply chain optimization model.

Sets	
I	Set of configurations or choices presented to a customer
K	Set of series
L	Set of demand regions
$K \times L$	Set of customer segments
M	Set of components
P	Set of supplier facilities
Q	Set of assembly plants
E	Set of economy of scale levels
W	Set of technology groups
R_w	Set of possible number of components to be offered in technology group $w \in W$
Parameters	
ω_{kl}	Size of the customer segment $kl \in K \times L$
ψ_{ikl}	Selling price of configuration $i \in I$ to a customer in segment $kl \in K \times L$
a_{ikl}	Attractiveness of configuration $i \in I$ to a customer in segment $kl \in K \times L$
$a_{\emptyset kl} > 0$	Attractiveness of outside alternatives for segment $kl \in K \times L$
C^S_{pw}	Facility cost of producing technology group $w \in W$ in supplier $p \in P$
C^T_{mp}	Tooling cost of producing component $m \in M$ in supplier $p \in P$
C^A_q	Fixed cost for the assembly plant $q \in Q$
LL_{mpe}	Lower break point wrt. economy of scale level $e \in E$ for component $m \in M$ in supplier facility $p \in P$
UL_{mpe}	Upper break point wrt. economy of scale level $e \in E$ for component $m \in M$ in supplier facility $p \in P$
$UL_{mp\|E\|}$	Capacity of supplier $p \in P$ for component $m \in M$
D_{mpe}	Savings from producing component $m \in M$ at economy of scale level $e \in E$ in supplier $p \in P$
c^S_{mpeq}	Unit cost of producing component $m \in M$ in supplier $p \in P$ at economy scale level $e \in E$ and shipping to assembly plant $q \in Q$
c^A_{iklq}	Unit cost of assembling configuration $i \in I$ for customer segment kl in assembly facility $q \in Q$
C^V_m	Engineering and integration cost for component $m \in M$ chosen for the program
C^O_{wr}	Complexity cost for selecting $r \in R_w$ components from the technology group $w \in W$
b^1_{mw}	1 if the component $m \in M$ is a member of technology group $w \in W$
b^2_{im}	1 if configuration $i \in I$ requires component $m \in M$
Variables	
x_{ikl}	1 if configuration $i \in I$ is offered to customer segment $kl \in K \times L$, and 0 otherwise.
z^S_{pw}	1 if technology group $w \in W$ is produced in supplier $p \in P$, and 0 otherwise
z^T_{mp}	1 if component $m \in M$ is produced by supplier facility $p \in P$, and 0 otherwise
z^A_q	1 if the assembly plant $q \in Q$ is selected, and 0 otherwise
z_{mpe}	1 if the supplier $p \in P$ produces component $m \in M$ at economies scale level $e \in E$
y^S_{mpeq}	Flow volume of component $m \in M$ produced in supplier $p \in P$ at economy of scale level $e \in E$ and shipped to assembly plant $q \in Q$
y^A_{iklq}	Flow volume of configuration $i \in I$ for customer segment $kl \in K \times L$ assembled in facility $q \in Q$
z^V_m	1 if component $m \in M$ is chosen for the program, and 0 otherwise
z^O_{wr}	1 if $r \in R_w$ components are selected from the technology group $w \in W$, and 0 otherwise

superscripts S, A, and T in the parameters and variables represent supplier, assembly, and tooling, respectively.

An *assortment* for a configurable product is the set of orderable configurations. Each *configuration* consists of an alternative selected for each *core* component (e.g., powertrain, seat, radio, etc.) as well as for some of the *optional* components (e.g., navigation, moonroof, etc.). For instance, a vehicle with 3.0-liter engine with All-Wheel Drive (AWD) and Automatic transmission with leather seats, high quality radio and navigation system and a vehicle with 2.0-liter engine with Front Wheel Drive (FWD) and Manual transmission with cloth seats, and mid-quality radio are two distinct configurations.

In our study, *technology group* refers to a set of alternative choices available for each core component. For instance, the powertrain technology group can involve alternative choices such as 2.0L-Manual-FWD, 2.0L-Auto-FWD, 2.5L-Auto-AWD, 3.0L-Auto-AWD and 3.5L-Auto-AWD. There is no technology group defined for optional components in our formulation. *Tooling* refers to the equipment and tools necessary to produce a given component. Tooling cost entails all costs such as capital and training etc. to achieve the production capability.

Customer choice is assumed to follow an MNL model (Guadagni & Little, 1983), where the purchase probability of configuration i in customer segment kl is expressed as:

$$\pi_{ikl}(\mathbf{x_{kl}}) = \frac{e^{U_{ikl}/\mu_{kl}} x_{ikl}}{e^{U_{\emptyset kl}/\mu_{kl}} + \sum_{i \in I} e^{U_{ikl}/\mu_{kl}} x_{ikl}},$$

where U_{ikl} is the utility of configuration i for segment kl, μ_{kl} is the customer heterogeneity parameter, and $\mathbf{x_{kl}}$ is the vector of decision variables for configurations offered to customers segment kl. In particular, we have $a_{ikl} = e^{U_{ikl}/\mu_{kl}}, \forall i \in I \cup \emptyset$ and purchase probability is equivalently represented as:

$$\pi_{ikl}(\mathbf{x_{kl}}) = \frac{a_{ikl} x_{ikl}}{a_{\emptyset kl} + \sum_{i \in I} a_{ikl} x_{ikl}}$$

Customers always have the option to walk away from the assortment and choose a competing product, i.e., $a_{\emptyset kl} > 0$. The mixed-integer fractional programming formulation for assortment planning problem is as follows:

$$\begin{aligned}
\text{Max} \ & \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} \frac{\omega_{kl} \psi_{ikl} a_{ikl} x_{ikl}}{a_{\emptyset kl} + \sum_{i \in I} a_{ikl} x_{ikl}} \\
& - \left(\sum_{p \in P} \sum_{w \in W} C^S_{pw} z^S_{pw} + \sum_{m \in M} \sum_{p \in P} C^T_{mp} z^T_{mp} + \sum_{q \in Q} C^A_q z^A_q \right) \\
& - \left(\sum_{m \in M} \sum_{p \in P} \sum_{e \in E} \sum_{q \in Q} c^S_{mpeq} y^S_{mpeq} + \sum_{i \in I} \sum_{k \in K} \sum_{l \in L} \sum_{q \in Q} c^A_{iklq} y^A_{iklq} \right. \\
& \left. - \sum_{m \in M} \sum_{p \in P} \sum_{e \in E} D_{mpe} z_{mpe} \right)
\end{aligned}$$

$$-\left(\sum_{m\in M} C_m^V z_m^V + \sum_{r\in R_w}\sum_{w\in W} C_{wr}^O z_{wr}^O\right) \tag{1}$$

$$\text{s.t. } \frac{\omega_{kl} a_{ikl} x_{ikl}}{a_{\emptyset kl} + \sum_{i\in I} a_{ikl} x_{ikl}} = \sum_{q\in Q} y_{iklq}^A, \ \forall i \in I, k \in K, l \in L \tag{2}$$

$$\sum_{e\in E} z_{mpe} = 1, \forall m \in M, p \in P \tag{3}$$

$$LL_{mpe} z_{mpe} \le \sum_{q\in Q} y_{mpeq}^S \le UL_{mpe} z_{mpe}, \ \forall m \in M, p \in P, e \in E \tag{4}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{l\in L} b_{im}^2 y_{iklq}^A = \sum_{p\in P}\sum_{e\in E} y_{mpeq}^S, \ \forall m \in M, q \in Q \tag{5}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{l\in L} y_{iklq}^A \le UL_q z_q^A, \ \forall q \in Q \tag{6}$$

$$\sum_{q\in Q} y_{mpeq}^S \le UL_{mpe} z_{mp}^T, \ \forall m \in M, p \in P, e \in E \tag{7}$$

$$z_{mp}^T \le \sum_{w\in W} b_{mw}^1 z_{pw}^S, \ \forall m \in M, p \in P \tag{8}$$

$$z_{mp}^T \le z_m^V, \ \forall m \in M, p \in P \tag{9}$$

$$\sum_{r\in R_w} z_{wr}^O = 1, \ \forall w \in W \tag{10}$$

$$\sum_{m\in M} b_{mw}^1 z_m^V = \sum_{r\in R_w} r z_{wr}^O, \ \forall w \in W \tag{11}$$

$$x_{ikl}, z_{pw}^S, z_{mp}^T, z_q^A, z_{mpe}, z_m^V, z_{wr}^O \in \{0, 1\} \tag{12}$$

$$y_{mpeq}^S, y_{iklq}^A \ge 0. \tag{13}$$

The objective function in (1) maximizes the profit, where the terms, respectively, represent the revenue from sales, fixed costs due to producing technology groups at supplier facilities, tooling costs for components at supplier facilities, fixed costs for assembly plants, total cost of producing components at supplier facilities and shipping them to assembly plants, total cost of assembling products at assembly plants and shipping them to the demand regions, savings due to economies of scale, engineering and integration cost of components, and complexity cost due to selecting multiple components from the same technology group. The equality constraints in (2) imply that the expected demand for the offered configurations is met. The constraints in (3) ensure that only one economy-of-scale level is selected, based on which the lower and upper bounds on the production for each component in each supplier facility are formulated in (4). The balance constraints between assembly plants and supplier facilities are formulated in (5), whereas the inequalities in (6) and (7) represent the capacity restrictions for assembly plants and supplier facilities, respectively. The restrictions in (8) ensure that tooling for a component is not installed unless the supplier facility is identified to house the technology group that the component belongs to. The inequalities in (9) imply that the tooling for a component is not installed unless the component is engineered. The constraints in (10) restrict selection of only one complexity level for each technology group, whereas equalities in (11) ensure the technology complexity level matches the number of engineered components in the technology group. Binary and nonnegativity restrictions are imposed by (12) and (13), respectively. We note that constraints in (2), (5), (7), and (9) ensure that configuration i may be offered only if all the necessary components are selected and engineered for the program as well as facility and tooling investments are made for producing the necessary components.

The mixed-integer fractional formulation in (1)–(13) is equivalently formulated as a mixed-integer nonlinear program via Charnes–Cooper transformation (Bazaraa, Sherali, & Shetty, 2013). To this end, let $\tau_{kl} = \frac{1}{a_{\emptyset kl} + \sum_{i\in I} a_{ikl} x_{ikl}}$ and $\tilde{x}_{ikl} = x_{ikl}\tau_{kl}$. Then, the fractional term in the objective function in (1) is reformulated as

$$\sum_{i\in I}\sum_{k\in K}\sum_{l\in L} \omega_{kl}\psi_{ikl} a_{ikl}\tilde{x}_{ikl},$$

and the fractional constraints in (2) are replaced by the following linear constraints:

$$\omega_{kl} a_{ikl}\tilde{x}_{ikl} = \sum_{q\in Q} y_{iklq}^A, \ \forall i \in I, k \in K, l \in L.$$

In addition, the defining constraints for τ_{kl} and $\tilde{x}_{ikl}$ are added to the formulation:

$$\tau_{kl} a_{\emptyset kl} + \textstyle\sum_{i\in I} a_{ikl}\tilde{x}_{ikl} = 1, \ \forall k \in K, l \in L \tag{14}$$

$$\tilde{x}_{ikl} = x_{ikl}\tau_{kl}, \ \forall i \in I, k \in K, l \in L \tag{15}$$

$$\tau_{kl}, \tilde{x}_{ikl} \ge 0. \tag{16}$$

Next, the quadratic constraints in (15) are linearized via the following inequalities:

$$\tau_{kl} + \frac{x_{ikl}}{a_{\emptyset kl}} - \frac{1}{a_{\emptyset kl}} \le \tilde{x}_{ikl} \le \min\left(\frac{x_{ikl}}{a_{\emptyset kl}}, \tau_{kl}\right), \forall i \in I, k \in K, l \in L. \tag{17}$$

The complete equivalent mixed-integer linear formulation for assortment planning problem is given in Appendix B.

3.1. Sustainability considerations for automotive products

Mandatory and stricter emission reduction targets are being set by a growing number of countries. For example, while the EU legislation has set the current emissions target for cars sold in EU at 130 grams CO_2 per kilometer in 2015, which corresponds to a fuel consumption of 5.6 liters per 100 kilometer (or 42 miles per gallon), the target will be decreased to 95 grams CO_2 per kilometer by 2021. The automakers have to pay excess emission premiums if the average fleet CO_2 emission exceeds the target limit. Similarly, the Energy Tax Act of 1978 and the Gas Guzzler Tax in the U.S. have reduced production and purchase of fuel-inefficient cars. We aim to incorporate these restrictions within the strategic assortment planning problem using average fleet MPG and product use CO_2e emission constraints. Towards this end, let g_i^1 be the fuel economy of configuration $i \in I$ and $\mathcal{F}$ be an exogenous limit on the average fuel economy for a vehicle program. In the strategic assortment problem, y_{iklq}^A represents the annual production volume of configuration $i \in I$ for customer segment $kl \in K \times L$ assembled in facility $q \in Q$, which is equal to sales through the constraint in (2). The inequality in (18) ensures that the annual average fuel economy for a vehicle program is greater than or equal to the exogenous threshold, $\mathcal{F}$.

$$\sum_{i\in I, k\in K, l\in L, q\in Q} g_i^1 y_{iklq}^A \ge \mathcal{F} \sum_{i\in I, k\in K, l\in L, q\in Q} y_{iklq}^A \tag{18}$$

In our analysis, we utilize carbon dioxide equivalent[1] (CO_2e) metric to represent the potential global warming effects of all GHGs into the equivalent amount of CO_2. As is typical in the automotive industry, we allow the vehicle model to be offered under several "series" (e.g., the same model can be offered as a sedan (saloon), two-door coupé, wagon (estate), or even as a folding-roof convertible, all derived from essentially the same engineering frame). Let g_{ikl}^2 be the average CO_2e emitted over the product use cycle of configuration $i \in I$ for series $k \in K$ in demand region $l \in L$, and $\mathcal{G}$ be an exogenous limit on the amount of CO_2e emissions

[1] https://www3.epa.gov/climatechange/glossary.html

from product use per vehicle produced. The constraint in (19) imply that the average CO_2e emissions from product use per vehicle for the vehicles sold in a particular year is bounded by $\mathcal{G}$.

$$\sum_{i\in I,k\in K,l\in L,q\in Q} g^2_{ikl} y^A_{iklq} \le \mathcal{G} \sum_{i\in I,k\in K,l\in L,q\in Q} y^A_{iklq} \tag{19}$$

Many manufacturers are also adopting sustainable supply chain practices to reduce carbon footprint and broader environmental risk (see Pallaro et al., 2015 for more details). Along these lines, we introduce a supply chain CO_2e emission constraint that limits the average CO_2e emission for each vehicle produced, which includes emissions for producing raw materials, transportation, and assembly operations. Let $\mathcal{H}$ be an exogenous limit on CO_2e emissions from the supply chain per vehicle produced, g^3_{mpeq} be the unit CO_2e emitted if component $m \in M$ is produced in supplier $p \in P$ at economy of scale level $e \in E$ for assembly plant $q \in Q$, and g^4_{iklq} be the unit CO_2e emissions produced if configuration $i \in I$ is produced for series $k \in K$ and demand region $l \in L$ at assembly plant $q \in Q$. The constraints in (20) ensures that the CO_2e emission generated from the supply chain per vehicle produced for the vehicles sold in a particular year is limited by $\mathcal{H}$.

$$\sum_{m\in M,p\in P,e\in E,q\in Q} g^3_{mpeq} y^S_{mpeq} + \sum_{i\in I,k\in K,l\in L,q\in Q} g^4_{iklq} y^A_{iklq} \le \mathcal{H} \sum_{i\in I,k\in K,l\in L,q\in Q} y^A_{iklq} \tag{20}$$

4. Data considerations for sustainability modeling

4.1. Fuel efficiencies and product use emissions

The automotive industry is going through a major transformation due to the introduction of a number of technologies aimed at improving emissions and fuel-efficiency (e.g., cylinder deactivation, direct fuel injection, improved turbocharger technologies, engine start-stop technologies for stopping the engine at traffic lights, regenerative braking systems, improved catalytic converters, etc). Given that product assortment planning is done years ahead of producing the first vehicle, it is important that effective and accurate data is collected to inform the modeling activities. It is also the case that contracts with key suppliers are executed at the earliest stages of the product development cycle. Even though technologies are changing at a rapid pace and the production costs for some of the newer technologies are falling quickly with production experience and economies-of-scale (e.g., cost of lithium ion battery packs have come down by 33% between 2012 and 2015, Wesoff, 2016), the assortment planning process often relies on mature technologies with high technology readiness level (TRL $\gg$ 6) (Williamson & Beasley, 2011) and reliable cost estimates.

In our study, the fuel efficiencies for the various powertrains entertained during assortment planning are specified by interpolating data provided on Ford Motor Company's website.[2] Electric vehicle fuel efficiency is typically measured with MPGe (MPG equivalent), and we assume that 34 kilowatt-hours of electricity is used to produce each MPGe.[3] For each gallon of gasoline that is combusted, it is assumed that 20 pounds of CO_2e are emitted[4] and 1 kilowatt-hours of energy produces 1 pounds of CO_2e.[5] In addition, we assume that the powertrain variant employed within a configuration essentially determines the amount of product use CO_2e emissions. This is a reasonable assumption given that the weight of the vehicle besides the powertrain is relatively constant, barring subtle differences due to other options such as types of seats and optional content selected. Table 2 displays fuel efficiencies and product use CO_2e emissions assumed for the different powertrain variants.

Table 2
Fuel efficiency and product use CO_2e of powertrain variants.

Powertrain variant	Fuel efficiency	Product use CO_2e (10^3 pounds)
2.0L Manual FWD	27 MPG	92.59
2.0L Manual AWD	26 MPG	96.15
2.0L Auto FWD	28 MPG	89.29
2.0L Auto AWD	27 MPG	92.59
2.5L Manual FWD	22 MPG	104.17
2.5L Manual AWD	21 MPG	108.7
2.5L Auto FWD	23 MPG	100
2.5L Auto AWD	22 MPG	104.17
3.0L Auto FWD	23 MPG	108.7
3.0L Auto AWD	22 MPG	113.64
3.5L Auto FWD	21 MPG	119.05
3.5L Auto AWD	20 MPG	125
Hybrid	47 MPG	53.19
Plug-In Hybrid	100 MPGe	42.5
Fully Electric	110 MPGe	38.64

4.2. Supply chain footprint and emissions

Padgett, Steinemann, Clarke, and Vandenbergh (2008) analyze several different carbon footprint calculators that aim to estimate GHG emissions based on activity. They find large differences in the carbon footprint estimates even for common input parameters and the inner-workings of the models have little visibility to explain the differences. One of the widely used calculators is the on-line economic input-output life-cycle assessment (EIO-LCA)[6] tool developed by the Green Design Institute at Carnegie Mellon University. It builds on the pioneering work done by Nobel Laureate Wassily Leontief (Leontief, 1970) and a detailed description of the method can be found in Hendrickson, Horvath, Joshi, and Lave (1998). The online tool estimates resource usage and emissions throughout the supply chain for various products, processes, materials, and industries. For instance, the tool considers the impact of all the parts that are needed to build the car, such as mining metal ores, producing windshields and electronic parts, in addition to the impact of final assembly operations. The online tool applies EIO-LCA method to various national economies, including U.S., Canada, Germany, and Spain, by utilizing national economic models as well as resource usage and emission data.

The EIO-LCA tool uses aggregate data at the national or state level for its calibration and estimation. If the automaker has access to better information regarding its suppliers and logistics solution providers, including its own facilities and power providers, it will lead to more accurate analysis and guidance. While this type of information is still not readily available to many automakers, increased participation is observed by OEMs in the Global Reporting Initiative.[7]

Supply chain emissions are frequently broken down into different "Scopes" when reported.[8] Scope 1 emissions are produced by the company's directly owned equipment and activities. Scope 2

[2] http://www.ford.com/, Accessed: July 2012.
[3] http://www.csmonitor.com/Innovation/2011/1225/Electric-cars-101-What-does-MPGe-mean-exactly
[4] http://www.peoplesworld.org/a-gallon-of-gas-makes-20-pounds-of-co2/
[5] http://www.stewartmarion.com/carbon-footprint/html/carbon-footprint-kilowatt-hour.html
[6] www.eiolca.net
[7] GRI is an international independent organization that helps businesses, governments and other organizations understand and communicate the impact of business on critical sustainability issues such as climate change, human rights, corruption and many others. https://www.globalreporting.org/Pages/default.aspx
[8] http://www.thecarbonreport.com/carbon-footprint-definition/

emissions are from purchased electricity or other energy, whereas Scope 3 emissions are associated with the product from 3rd parties, such as suppliers. From the EIO-LCA website, we gather the following emission information for the U.S. and China with the format [CO_2e emissions (metric tons per million dollars of activity): Scope 1% – Scope 2% – Scope 3%], as follows:

U.S.	Automotive Manufacturing	[563: 2% – 32% – 66%]
U.S.	Motor Vehicle Parts Manufacturing	[757: 3% – 31% – 66%]
U.S.	Broadcast and Wireless Communications Equipment	[322: 3% – 43% – 54%]
China	Motor Vehicles	[2240: 4% – 40% – 55%]
China	Communication Equipment	[1870: 1% – 44% – 55%]

Both the U.S. and China models on the EIO-LCA website are calibrated using producer economic and environmental data from 2002. Given that emission rates have likely fallen since 2002 due to industry efforts to improve sustainability, we recommend product assortment planners to rely on more current data. Our goal however is to simply demonstrate the power of assortment planning models rather than analysis of data for a specific real-world vehicle program.

We utilize "Broadcast and Wireless Communications Equipment" and "Communication Equipment" categories, respectively, in the U.S. and China models for the electronic components of the vehicle. The three radio variants and navigation system are classified as electronic components, while powertrains, seats, moonroof fall under standard "Motor Vehicle Parts Manufacturing" category.

The assortment planning model only accounts for optional parts and components and the design for rest of the vehicle (e.g., chassis, frame and sheet metal panels, bumpers etc) is assumed to be finalized and carries fixed content. In our analysis, in consultation with SMEs from the automotive industry, we made the assumption that 60% of the total CO_2e emissions throughout the supply chain can be apportioned to the fixed content of the vehicle and the rest to optional parts and components within the decision variable scope of the assortment planning model.

For standard parts manufacturing in China, we assume that the same ratio between the U.S. final assembly and U.S. parts manufacturing can also be applied to China. Even though we do not have access to EIO-LCA data for Mexico, it is known that Mexico's usage ratio of fossil fuels to renewable energy and nuclear is similar to the U.S., due to large amounts of geothermal energy sources.[9] We assume that production in Mexico will lead to 10% higher CO_2e emissions per dollar than U.S., with Scope percentages that fall between the U.S. and China. The indirectly estimated supply chain emission data is as follows:

China	Motor Vehicle Parts Manufacturing	[3011: 7% – 38% – 55%]
Mexico	Automotive Manufacturing	[619: 3% – 36% – 61%]
Mexico	Motor Vehicle Parts Manufacturing	[832: 5% – 35% – 60%]
Mexico	Broadcast and Wireless Communications Equipment	[354: 2% – 43% – 55%]

5. Experimental results

In this section, we individually add sustainability constraints in (18)–(20) to the base assortment planning model in (1)–(13), and analyze the behavioral changes in the profit, expected sales, average MPG, as well as product use, supply chain, and Scopes 1, 2, 3 CO_2e emissions as the sustainability requirements are tightened. The resulting variables of interest are presented as a percentage of the "base case" model solution.

Our illustrative example is motivated by a mid-size segment program of a leading global OEM targeting the U.S. and Canadian markets and it can be readily extended to other markets and subregions. Within the example, assortment vehicle configuration is identified by choices for powertrain, radio, seat, moonroof, and navigation subsystems, and the utility of a configuration is assumed to be the sum of utilities of the individual components (the rest of the vehicle content is assumed to be fixed). The case study involves 15 powertrains (2.0L, auto/manual, FWD/AWD; 2.5L, auto/manual, FWD/AWD; 3.0L, auto, FWD/AWD; 3.5L, auto, FWD/AWD; hybrid; plug-in hybrid; fully electric), 3 radios (low, mid, high), 6 seats (cloth, cloth 60–40, leather, leather 60–40, premium leather, premium leather 60–40), a moonroof option, and a navigation system option. The case study considers three suppliers in China, Mexico, and U.S. for each feature or option, and two assembly plants in Mexico and U.S. with 300K capacity/plant having two economies of scale levels. The demand for configurations with low, mid-low, mid-high, and high quality are represented with S, SE, SEL, and Titanium model series (a practice of our collaborator), for two demand regions (U.S. and Canada). For maintaining computational tractability, we characterize customer choice within each series segment by an MNL model and that customers do not switch between series segments. While a nested-MNL model will provide further flexibility by allowing customers to switch between series, computational tractability is lost limiting the examples to trivial assortment problems with relatively few configurations whereas the automotive industry often plans core-entity configuration assortments in the 100s to even tens of thousands. For brevity and improved flow, the cost parameters, option prices, and other parameters and assumptions are listed in Appendix A.

The optimal solution to the "base line" case study results in a profit of $746.5 million. The powertrains, radios, seats, and moonroof are produced by the suppliers in Mexico, whereas navigation system is produced by the supplier in China (due to relatively high packaging density). The assembly plant in Mexico is selected and its full capacity is utilized for producing 300k vehicles. The model selects only three powertrains among the 15 options (2.0L auto FWD, 3.0L auto FWD, 3.5L auto FWD), whereas all three radios and six seat variants are chosen for producing in total of 209 configurations. The resulting product use CO_2e is 108.6k pounds per vehicle, whereas supply chain CO_2e is 32k pounds per vehicle with respective Scopes 1, 2, and 3 CO_2e emissions of 1.1k, 11.6k, and 19.3k pounds per vehicle.

All runs are conducted on a grid computing node having 2.6 gigahertz AMD processor with 64 gigabytes of RAM. The numerical instances, formulated as mixed-integer linear programming problems as in Appendix B, are solved using IBM ILOG CPLEX version 12.4 (IBM Ilog Cplex, 2011).

5.1. Vehicle program MPG target

Here we study the impact of tightening the vehicle program MPG target on the resulting assortment. The MPG constraint introduced in (18) is appended to the base model and the target level $\mathcal{F}$ is gradually increased from its base case solution value of 23 miles per gallon to 46 miles per gallon. It is observed that offering electrified vehicles (EVs) can raise the program MPG beyond the requirement at certain levels. In addition, total supply chain carbon emissions increase with the introduction of EVs, which is consistent with the literature.

In consultation with our global automotive collaborator, our model only considers EVs for customers in the SE series segment (a practice by this OEM). The numerical results show that in some cases it may be optimal for automakers to: 1) Use EVs as "loss leaders" to enable the continued selling of vehicles with large standard powertrains and 2) Limit the number of conventional powertrains offered to customer segments that are likely to consider electric powertrains, pushing customers towards electric powertrains by reducing possible substitutes.

[9] http://en.wikipedia.org/wiki/Electricity_sector_in_Mexico

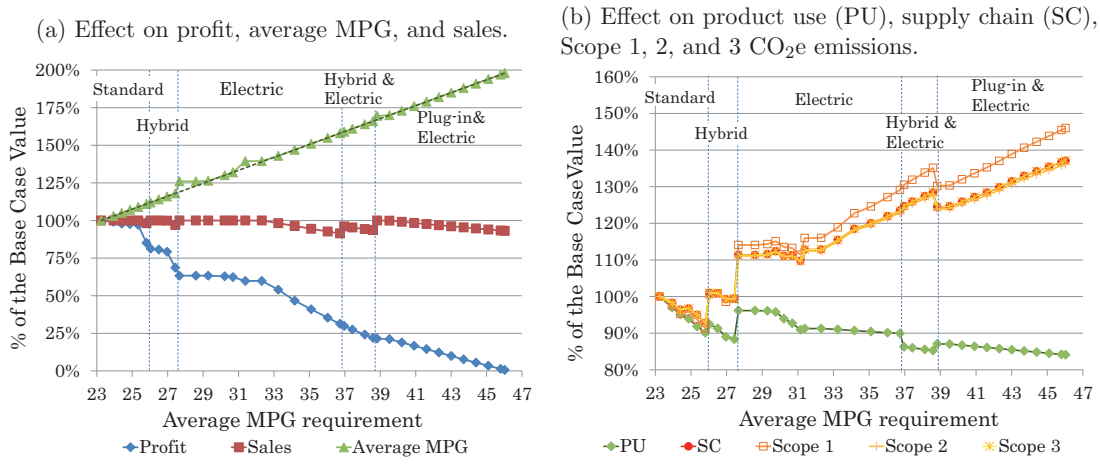

Fig. 1. Effect of average MPG requirement.

The behaviors of the variables of interest, profit, expected sales, program MPG, as well as product use, supply chain (Scopes 1, 2, 3) CO_2e emissions, are significantly different for various ranges of program MPG requirements. For discussion, as illustrated in Fig. 1, the feasible MPG requirement domain is divided into five ranges based on the selected powertrains.

In the *standard range* in Fig. 1, only standard powertrains are utilized to reach the target MPG. Powertrain sizes move towards the smaller options that are still popular in each series (such as the 3.0L Auto AWD powertrain in the Titanium series instead of the originally chosen 3.5L Auto FWD powertrain) and sales target still remains at 300k vehicles, using the full capacity at the assembly plant. Through the end of this range, further powertrain size reduction is not enough to attain the targeted MPG while keeping the target sales at its maximum. The model suggests reducing the sales by approximately 5600 vehicles (mainly for the configurations with 3.0-liter powertrains offered to SEL series). This strategy is significantly costly and it reduces the profit to 85% of the base case, in comparison to 95% with the previous MPG target. The system is strained and offering an alternative powertrain becomes inevitable if we further tighten the MPG requirement. In the *standard range*, product use and supply chain, including Scopes 1, 2, and 3, CO_2e emissions have decreasing trends.

In the *hybrid range* in Fig. 1, the hybrid powertrain is selected for production in addition to the standard powertrains, which creates a jump in program MPG and a nearly flat profit graph immediately after. Initially, the addition of the hybrid creates enough slack between the MPG requirement and the realized MPG to allow assortments in the SEL and Titanium to reset to the choices that were present in the base case (more configurations and larger engines). Supply chain CO_2e emissions rise as sales increase slightly and hybrid powertrain is produced, which creates more supply chain emissions than the standard ones. However, with some SE customers substituting from standard engines to the lower product use emission hybrid, average product use emissions are lower than the base case even though it increases in comparison to the last MPG target in the standard range. As the MPG requirement is tightened within this range, the same changes that occurred in standard range are observed. The model suggests selecting configurations with smaller engine sizes while still targeting sales of 300k. When this strategy is no longer adequate, the sale of configurations with larger engines are limited and the total target sales drops below the capacity. Similar to the standard range, this strategy is costly and puts significant pressure on profit.

In the *electric range* in Fig. 1, the fully electric powertrain is selected for production in addition to the standard powertrains. This instantly raises the program MPG from about 27 to 29. The same solution is provided until the MPG requirement reaches to 29. Further MPG increases are met by increasing the number vehicles supplied with fully electric engine. When it is not enough or costly, smaller sized powertrains are replaced the larger ones. When the MPG requirement reaches approximately 31.4 miles per gallon, configurations with standard engines start to be eliminated from the SE series. The SE assortment changes from having two standard powertrains plus the fully electric to just having a single standard powertrain and the fully electric. This increases the sales of the fully electric from approximately 24k to 29k. However, total sales in the SE series between the U.S. and Canada fall from 112k to 102k. With the single standard powertrain in the SE series combined with a fully electric powertrain, it is now profitable to add a second engine to the Titanium series (both a 3.0L Auto AWD and a 3.5L Auto AWD are now offered), increasing demand coverage in that series from 72% to 80%. As the MPG requirement is further tightened throughout the electric range, fewer standard powertrain configurations are offered in the SE series, resulting in lower overall expected sales in the series but with a higher proportion having a fully electric powertrain.

In the electric range, product use CO_2e emissions decrease due to fuel efficient powertrains. On the other hand, total supply chain emissions increase over the base case, as electrified powertrains create more supply chain carbon than standard powertrains. A separation in the Scope 1 emissions from the other scopes is also observed starting in this range. For the base case model, some configurations that do not include a moonroof and/or navigation system are not offered, as they have lower selling prices and compete with other configurations with smaller sized powertrains the manufacturer can offer. As the MPG requirement is further increased, it becomes important for the manufacturer to offer the full set of configurations created from certain engines to meet the requirement, including configurations without a navigation system. Because the navigation system is an electronic component, it has a lower percentage of its emissions attributed to Scope 1 than standard components. Thus, with fewer navigation systems being produced, there is a higher percentage of Scope 1 emissions. Because Scope 1 emissions are on a much smaller scale than Scopes 2 and 3 emissions, the effect is magnified in comparison.

In the *hybrid and electric range* in Fig. 1, hybrid powertrains are produced in addition to the fully electric and standard powertrains. Supply chain carbon emissions increase as the manufacturer now chooses to supply the hybrid powertrain in addition to the fully electric. The model continues to protect the sales of the SEL and Titanium series (approximately 80% coverage rate) at the cost of the SE series (approximately 50% coverage rate). Improved MPG is achieved by offering fewer configurations in the SE series

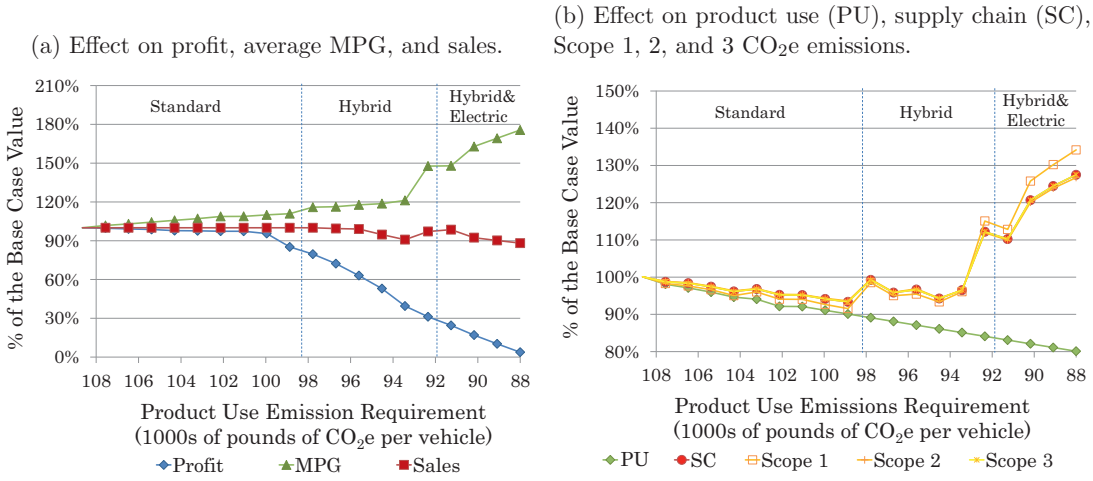
(a) Effect on profit, average MPG, and sales.
(b) Effect on product use (PU), supply chain (SC), Scope 1, 2, and 3 CO2e emissions.
% of the Base Case Value
Standard
Hybrid
Hybrid& Electric
Product Use Emission Requirement (1000s of pounds of CO2e per vehicle)
Profit
MPG
Sales
Product Use Emissions Requirement (1000s of pounds of CO2e per vehicle)
PU
SC
Scope 1
Scope 2
Scope 3

Fig. 2. Effect of product use CO_2e requirement.

with standard powertrains, forcing customers to either choose electrified powertrains or walk away.

In the *plug-in and electric range* in Fig. 1, plug-in powertrains are introduced in addition to the fully electric and standard powertrains. The model protects the S, SEL and Titanium series, whereas a constant decrease is observed for the SE series. Demand coverage of 64% at the beginning of this range, drops to 50% at the end for the SE series. The total expected sales and the profit decrease throughout the range. Approximately at a MPG requirement of 46, the business becomes unprofitable and no vehicles are produced.

5.2. Product use CO_2e target

Here we study the impact of product use emissions targets on the assortment. The program product use CO_2e restriction defined in (19) is added to the base model. The target product use CO_2e $\mathcal{G}$ is gradually decreased from its base case solution value of 108k pounds per vehicle to 88k pounds per vehicle, beyond which the automaker is unable to create any profit and ceases production (Fig. 2). As the product use CO_2e target is tightened, it is seen that automaker initially offers configurations with smaller sized powertrains, then introduces the hybrid engine, and finally supplies electrified vehicles in order to push customers towards buying them, while trying to recoup lost sales in the SE series in the SEL and Titanium series. For more stringent targets, the automaker chooses not to utilize full capacity in order to meet the CO_2e target. Restricting product use emissions can lead to relatively higher supply chain emissions, as electric vehicles produce more carbon in the supply chain phase. Since the product use is much larger than supply chain CO_2e, even under a cradle-to-gate analysis, the net is a reduction in overall GHG emissions. We model EVs gaining power from the current power grid in place in the U.S. and Canada. If these power sources were to generate electricity using more renewable energy and fewer fossil fuels, the results would be different and the manufacturer could produce under more stringent product use emission requirements and still be profitable. For discussion, the feasible product use CO_2e requirement domain is divided into three ranges based on the selected powertrains: Standard, Hybrid, and Hybrid&Electric.

In the *standard range* in Fig. 2, the model substitutes smaller, but still popular powertrains in place of larger ones to improve the product use CO_2e emissions without reducing the profit significantly. Despite all these changes, the demand coverage rate remains between 70% and 80%, depending on the combination of options chosen. Through the end of the standard range, another standard powertrain is added to meet the product use CO_2e emissions target. However, fixed costs due to this additional powertrain reduces the profit significantly. In the standard range, total expected sales stays at its maximum, bounded by the capacity of the assembly plant and supply chain, whereas Scopes 1, 2, and 3 CO_2e emissions follow a decreasing trend.

In the *hybrid range* in Fig. 2, the hybrid powertrain is chosen for the SE series throughout the range. The peaks and valleys of the supply chain CO_2e emissions can be explained through differences in the SE and SEL series. The SEL series starts with 2.0L and 3.0L Auto AWD. When the product use CO_2e threshold drops to 95K pounds per vehicle, a 2.5 Auto AWD is substituted for the 3.0L Auto AWD. At 94k pounds per vehicle, only a 2.0 Auto AWD is offered to the SEL series, and expected sales begin to fall. Depending on the amount of expected sales in the SE series, the model has to offer a certain number of hybrids to keep the average product use CO_2e emissions under the threshold, causing supply chain carbon to rise when more hybrids are produced.

In the *hybrid and electric range* in Fig. 2, we introduce the fully electric powertrain in addition to the existing standard and hybrid powertrains. As the product use CO_2e emissions threshold is tightened, the model offers fewer SE configurations with standard powertrains and pushes customers to configurations with hybrid and electrified vehicles, which enables it to make profit out of vehicles in the other series and still meet the product use CO_2e emissions threshold. This strategy reduces the demand coverage rate of SE customers from 70% to 51% through the range, resulting in significant number of walk aways and loss in revenue and profit. A higher Scope 1 emission is observed relative to the base case than Scopes 2 or 3 under a strong product use emissions requirement due to a lower percentage of the vehicles containing the navigation system.

5.3. Supply chain CO_2e target

The analysis for the effect of supply chain CO_2e target is conducted in two different settings: 1) the assortment is restricted to the assortment chosen in the base case and 2) the assortment is free to be changed. EVs are not used as a tool by the model to limit supply chain CO_2e emissions. This is intuitive, since electrified powertrains have higher supply chain emissions than standard powertrains.

An automaker can stay profitable under stricter supply chain GHG emission requirements by redesigning its assortment. In the case of fixed assortment, automaker is no longer profitable for

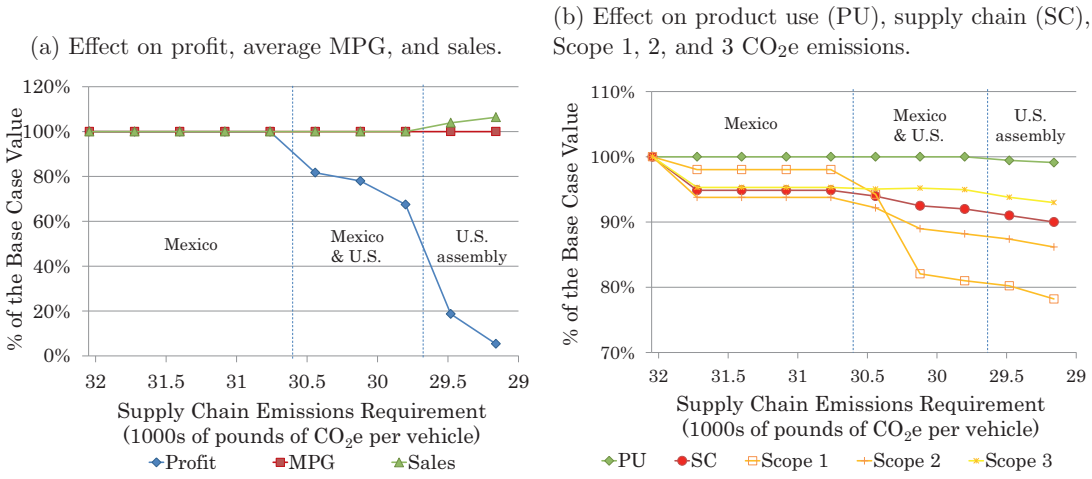

Fig. 3. Effect of supply chain CO_2e requirement (assortment fixed).

supply chain CO_2e targets below 29k pounds per vehicle. On the other hand, automaker stays profitable for stricter supply chain CO_2e targets by adjusting its assortment.

5.3.1. Supply chain CO_2e target (assortment fixed)

When the assortment is fixed, the model shifts production either from China to Mexico or from Mexico to the U.S., where less GHGs are produced per dollar spent in manufacturing in order to meet a tighter supply chain CO_2e requirement. In the *Mexico* range in Fig. 3, the production of the navigation system is moved from China to Mexico. The expected profit is reduced by approximately $500k, which is not significant compared to the original profit of $746.5 million. In the *Mexico and U.S.* range in Fig. 3, component supplier selection decisions are changed to meet the supply chain CO_2e emissions target. First, the production of radios, seats, navigation systems, and moonroof productions are moved to the U.S. Then, the model moved powertrains to U.S. and all other components to Mexico. Finally, production of radios, navigation systems, and moonroofs are also moved to the U.S. In the *U.S. assembly* range in Fig. 3, a second assembly plant is opened in the U.S. to meet the supply chain CO_2e emissions target. With an initial cost of $300 million, the profit drops significantly. In order to meet further decreases in the supply chain CO_2e emission target, more of the component production and vehicle assembly are moved to the U.S.

5.3.2. Program supply chain CO_2e target (assortment free)

When the assortment is free, the model substitutes smaller powertrains for larger ones in addition to moving production either from China to Mexico or from Mexico to the U.S. to meet the supply chain CO_2e target. In the *Mexico range* in Fig. 4, navigation system production is moved from China to Mexico as in the case of fixed assortment. In the *assortment change* range in Fig. 4, the automaker offers configurations with smaller, but still popular, powertrains instead of larger ones, since the production of smaller powertrains release less CO_2e. Total sales remains almost constant at its maximum. However, the sale of smaller powertrains with lower profit margins causes profits to decrease. Through the end of this range, the number of configurations offered to customers in Titanium series along with the demand coverage are decreased to meet the supply chain CO_2e emission target. In the *U.S.* range Fig. 4, the production of powertrains and moonroof are moved from Mexico to the U.S., while radio, seat, and navigation system are produced and vehicles are assembled in Mexico. Even though it allows to offer more configurations for some series, the model is still extremely constrained by the supply chain emissions target, and the expected total sales drops throughout the range. When the target reaches 25.6k pounds of CO_2e, the demand coverage for the Titanium series customers drops below 30%, whereas S series customers are covered by a rate of more than 90%. Any further tightening of the target makes the business unprofitable.

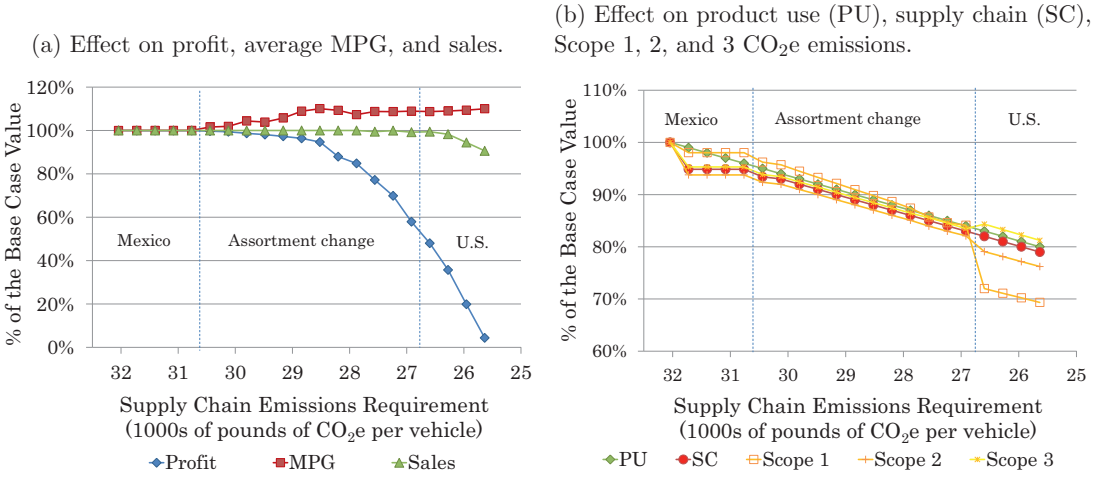

Fig. 4. Effect of supply chain CO_2e requirement (assortment free).

6. Conclusion and future directions

We introduced assortment planning models for automotive products that can provide effective decision support and directional guidance to strategic product planners. The models account for constraints that stem from environmental regulations and broader sustainability goals of the firm in the form of program MPG requirement as well as supply chain and product use emissions targets while balancing vehicle program profitability. The practical utility of these models is also illustrated through a case study developed in collaboration with a leading global automaker.

There are several possibilities for future research. Rather than managing the environmental and sustainability goals through constraints while maximizing program profitability, multi-objective optimization methods can be employed to establish the complete Pareto front of optimal solutions. However, we believe that work could be better served to increase the fidelity of the data inputs. For example, more effective tools and processes are necessary to improve estimation of manufacturing and supply chain complexities that stem from large assortments with shared systems. There is also need to improve characterization of customer choice within assortment planning models while maintaining computational tractability. There is always the need to improve emissions calculators. Future research can also investigate the value of stochastic models to deal with technology, demand, and manufacturing cost uncertainties. Lastly, companies often rely on "platforms" for deriving product variants. For example, the same platform might be employed for designing a mid-size sedan and a cross-over vehicle. Product assortment planning can thus focus on platform optimization for promoting sustainability of derivative products with overlapping design, manufacturing, and supply/distribution networks.

Acknowledgment

Our special gratitude goes to Gintaras Puskorius and Dean Pichette of Ford Motor Company for their valuable insights and constructive directions, which were very helpful in shaping this research. We would also like to thank three anonymous reviewers and guest editor for their supportive and constructive comments, which have greatly helped improve the substance and presentation of this paper.

Appendix A. Key data parameters

Pricing

Base price: S: $16,000 SE: $18,000 SEL: $20,000 T: $22,000

Option prices:

Powertrain:	2.0L Manual FWD: $2500	2.5L Manual FWD: $3000	3.0L Auto FWD: $4500
	2.0L Manual AWD: $3400	2.5L Manual AWD: $3900,	3.0L Auto AWD: $5800
	2.0L Auto FWD: $3000	2.5L Auto FWD: $3500	3.5L Auto FWD: $5,500
	2.0L Auto AWD: $3900	2.5L Auto AWD: $4800	3.5L Auto AWD: $6,800
	Hybrid: $10,000	Plug-In Hybrid: $17,000	Fully Electric: $23,000
Radio:	Low Radio: $100	Mid Radio: $300	High Radio: $800
Seat:	Cloth: $300	Leather: $1000	Premium Leather: $1200
	Cloth 60/40: $400	Leather 60/40: $1100	Premium Leather 60/40: $1300

Moonroof: $600

Navigation system: $1000

- MSRP: Series base price + Option prices
- MSRP discount: 90% of MSRP
- Configuration selling price (ψ_{ikl}) = MSRP discount $\times$ (MSRP)

MNL demand model parameters

Total customers (w_{kl}):	U.S.	S: 36,000	SE: 144,000	SEL: 108,000	T: 72,000
	Canada	S: 4000	SE: 16,000	SEL: 12,000	T: 8000
Walk utility (a_{ykl}):	U.S. and Canada	S: 7	SE: 400	SEL: 400	T: 400

In the illustrative example, per common industry practice, configurations offered in the lowest S segment are priced to be extremely good bargains (often such segment vehicles are seen as "loss leaders" and are mostly made available by OEMs to help dealers advertise these bargain vehicles to drive customer traffic to dealerships). Therefore, with guidance from the SMEs, we parameterized the demand model such that even the availability of just a few vehicle configurations would cover majority of the demand in this segment. On the other hand, the demand model is parameterized to represent somewhat stiff competition in SE, SEL, and Titanium segments. Accordingly, in consultation with SMEs, we assign 7, 400, 400, and 400 as representative walk away utilities for S, SE, SEL, and Titanium series (higher walk away utilities correspond to stiffer segment competition). Note that the walk away utilities for the latter three segments serve the purpose of differentiating the demand model response and thereby the assortment results from those of the lowest segment S.

The products are vertically differentiated with fixed prices and it is assumed that feature and option utility can be parameterized as a function of price within each model series (e.g., customer for the Titanium series might be less price sensitive for a higher end feature than customers targeting the lower end model series). It is also assumed that the automaker logically prices options so that each series has options that appeal to customers with different reservation prices (grouped by series). Fig. A.5 displays the attractiveness values for 12 standard powertrains in each series, as parameterized in the case study. The dashed lines represent the relation between the price of a powertrain and attractiveness for consumers in each series, whereas the markers demonstrate the price-attractiveness points associated with the 12 standard powertrains. For instance, 2.5L-Auto-AWD powertrain, labeled as P8, costs $4800, for which attractiveness values are 0.4, 17.3, 23.2, and 6.4 for consumers in S, SE, SEL, and T segments, respectively. P8 powertrain provides high utility for consumers in SE and SEL segments, whereas the utility is low due to its high cost and low power, respectively, for consumers in S and T segments. In addition, we set the attractiveness of a component to zero, if it is below a threshold. The attractiveness values for radio and seat options, as well as moonroof and navigation system for consumers in each segment are displayed in Table A.3. Marketing group should exercise caution to ensure that these utility functions are well specified to reflect the preferences of customers.

The attractiveness of a configuration is modeled as the summation of attractiveness of its individual components. The configurations that involve a component with no attractiveness for a segment are not offered in the segment. For instance, moonroof has no attractiveness value for consumers in S segment. Hence, configurations that involve moonroof are not offered in S segment.

Estimating utilities of attributes and products are among the most challenging tasks for businesses. In particular, OEMs rely on external market research firms, consumer clinics, as well as methodologies such as conjoint analysis (Green & Srinivasan, 1978) for component and configuration utilities and attractiveness.

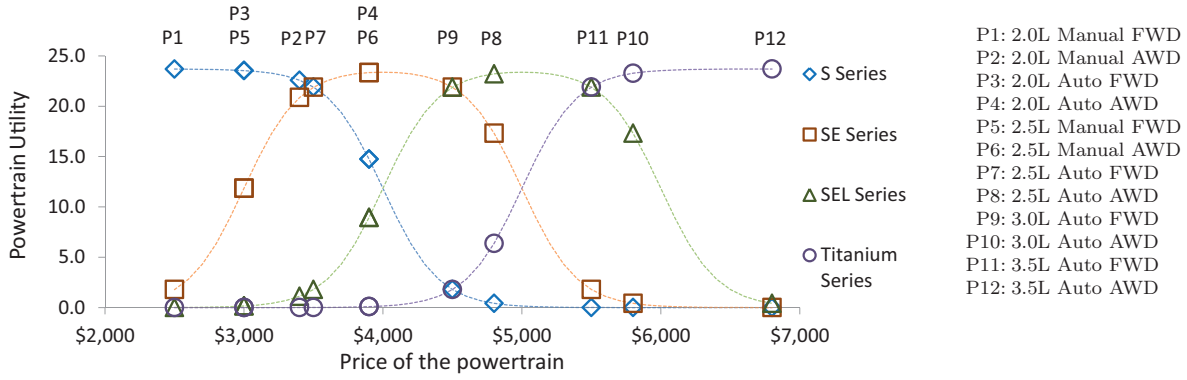

Fig. A5. Illustrative example of parameterizing utilities for powertrains.

Table A3
Component attractiveness values for each series.

Components	Price	S series	SE series	SEL series	Titanium series
Low radio	$100	2.82	1.43	0	0
Mid radio	$300	1.44	2.48	2.1	1.44
High radio	$800	0	0	2.53	2.82
Cloth	$300	5.37	0	0	0
Cloth 60/40	$400	5.99	3.05	0	0
Leather	$1000	5.37	5.37	0	0
Leather 60/40	$1100	3.05	3.05	3.04	3.05
Premium leather	$1200	0	0	5.26	5.98
Premium leather 60/40	$1300	0	0	3.04	5.98
Moonroof	$600	0	1.34	2.58	4.23
Navigation system	$1000	0	1.93	4.3	7.05

Conjoint analysis is extensively utilized in automotive industry for understanding consumer valuations of various attributes (components) of a product or service (configuration) using survey-based techniques. Based on the consumer preferences, perceived valuations of individual components are estimated to create models for market share, revenue, and profitability analysis.

Manufacturing and transportation costs

- Configuration unit cost percentage (% of the selling price): Mexico 50%, U.S. 60%
- Component unit cost percentage (% of the selling price): China 35%, Mexico 40%, U.S. 50%
- Duties: China 5% (no duty cost for Mexico and U.S.)
- Economies of scale multiplier: Low 100 %, High 90%
- Unit cost of transportation: $2 per mile per container
- Number of configurations/container: 10
- Number of components/container: Powertrain:36, Radio:1000, Seat:18, Moonroof:120, Navigation system:1000
- Distance from assembly plant to demand region (d_{ql}, in miles): Mexico to U.S. 1200, Mexico to Canada 1600 , U.S. to U.S. 600, U.S. to Canada 800
- Distance from component supplier to assembly plant (d_{pq}, in miles): China to Mexico 7700, China to U.S. 7450, Mexico to Mexico 0, Mexico to U.S. 1800, U.S. to Mexico 1800, U.S. to U.S. 0

Configuration unit cost (c^A_{ilkq})

Configuration unit cost % × Selling price + $\frac{d_{ql} \times \text{Price/Mile}}{\text{Configurations per container}}$

Component unit cost (c^S_{mpeq})

Economy of scale multiplier × (Duty + Component unit cost % × Selling price + $\frac{d_{pq} \times \text{Price/Mile}}{\text{Components per container}}$)

Capacities

- Facility capacity (UL_q, UL_{mp2}) – 300,000
- Economies of scale level break point (UL_{mp1}) – 100,000

Facility costs for assembly plants (C^A_q) *and component suppliers* (C^S_{pw}), *in millions*

Assembly plant:		Mexico: $250	U.S.: $300
Engine facility:	China: $100	Mexico: $110	U.S.: $120
Radio facility:	China: $5	Mexico: $5.5	U.S.: $6
Seat facility:	China: $15	Mexico: $16.5	U.S.: $18

Tooling costs (C^T_{mp}), *in millions*

Standard powertrain:	China: $5	Mexico: $5.5	U.S.: $6
Hybrid powertrain:	China: $2.5	Mexico: $3.0	U.S.: $3.5
Plug-in powertrain:	China: $3	Mexico: $3.5	U.S.: $4
Fully electric powertrain:	China: $4	Mexico: $4.5	U.S.: $5
Radio:	China: $0.5	Mexico: $0.55	U.S.: $0.6
Seat:	China: $1.5	Mexico: $1.65	U.S.: $1.8
Moonroof:	China: $25	Mexico: $27.5	U.S.: $30
Navigation system:	China: $25	Mexico: $27.5	U.S.: $30

Complexity costs – Function of number of part variants (C^O_{wr}), *in millions*

Powertrain:	1: 0	2: $7	3: $10.5	4: $15.7	5: $23.6	6: $35.4	7: $53.1	8: $79.7
	9: $119.6	10: $179.4	11: $269.1	12: $403.6	13: $908	14: $1,300	15: $2,000	
Radio:	1: 0	2: $0.7	3: $1.1					
Seat:	1: 0	2: $1.7	3: $2.6	4: $3.9	5: $5.9	6: $8.8		

Engineering and development costs (C^V_m), *in millions*

Powertrain:	2.0L Manual FWD: $30	2.5L Manual FWD: $36	3.0L Auto FWD: $48
	2.0L Manual AWD: $36	2.5L Manual AWD: $42	3.0L Auto AWD: $54
	2.0L Auto FWD: $36	2.5L Auto FWD: $42	3.5L Auto FWD: $60
	2.0L Auto AWD: $42	2.5L Auto AWD: $48	3.5L Auto AWD: $66
	Hybrid: $130	Plug-In Hybrid: $300	Fully Electric: $300
Radio:	Low Radio: $1.5	Mid Radio: $2.7	High Radio: $4.5
Seat:	Cloth: $1.5	Leather: $1.8	Premium Leather: $2.1
	Cloth 60/40: $2.1	Leather 60/40: $2.4	Premium Leather 60/40: $2.7

Moonroof: $3.6
Navigation system: $5.4

Appendix B. Mixed-integer linear formulation

The mixed-integer linear programming formulation of the assortment planning problem is as follows:

$$\text{Max} \quad \sum_{i\in I}\sum_{k\in K}\sum_{l\in L}\omega_{kl}\psi_{ikl}a_{ikl}\tilde{x}_{ikl} - \left(\sum_{p\in P}\sum_{w\in W}C^S_{pw}z^S_{pw} + \sum_{m\in M}\sum_{p\in P}C^T_{mp}z^T_{mp} + \sum_{q\in Q}C^A_q z^A_q\right) - \left(\sum_{m\in M}\sum_{p\in P}\sum_{e\in E}\sum_{q\in Q}c^S_{mpeq}y^S_{mpeq} + \sum_{i\in I}\sum_{k\in K}\sum_{l\in L}\sum_{q\in Q}c^A_{iklq}y^A_{iklq} - \sum_{m\in M}\sum_{p\in P}\sum_{e\in E}D_{mpe}z_{mpe}\right) - \left(\sum_{m\in M}C^V_m z^V_m + \sum_{r\in R_w}\sum_{w\in W}C^O_{wr}z^O_{wr}\right) \tag{B.1}$$

$$\text{s.t. } \omega_{kl}a_{ikl}\tilde{x}_{ikl} = \sum_{q\in Q}y^A_{iklq}, \ \forall i\in I, k\in K, l\in L \tag{B.2}$$

$$\sum_{e\in E}z_{mpe} = 1, \forall m\in M, p\in P \tag{B.3}$$

$$LL_{mpe}z_{mpe} \le \sum_{q\in Q}y^S_{mpeq} \le UL_{mpe}z_{mpe}, \ \forall m\in M, p\in P, e\in E \tag{B.4}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{l\in L}b^2_{im}y^A_{iklq} = \sum_{p\in P}\sum_{e\in E}y^S_{mpeq}, \ \forall m\in M, q\in Q \tag{B.5}$$

$$\sum_{i\in I}\sum_{k\in K}\sum_{l\in L}y^A_{iklq} \le UL_q z^A_q, \ \forall q\in Q \tag{B.6}$$

$$\sum_{q\in Q}y^S_{mpeq} \le UL_{mpe}z^T_{mp}, \ \forall m\in M, p\in P, e\in E \tag{B.7}$$

$$z^T_{mp} \le \sum_{w\in W}b^1_{mw}z^S_{pw}, \ \forall m\in M, p\in P \tag{B.8}$$

$$z^T_{mp} \le z^V_m, \ \forall m\in M, p\in P \tag{B.9}$$

$$\sum_{r\in R_w}z^O_{wr} = 1, \ \forall w\in W \tag{B.10}$$

$$\sum_{m\in M}b^1_{mw}z^V_m = \sum_{r\in R_w}rz^O_{wr}, \ \forall w\in W \tag{B.11}$$

$$\tau_{kl}a_{\emptyset kl} + \sum_{i\in I}a_{ikl}\tilde{x}_{ikl} = 1, \ \forall k\in K, l\in L \tag{B.12}$$

$$\tau_{kl} + \frac{x_{ikl}}{a_{\emptyset kl}} - \frac{1}{a_{\emptyset kl}} \le \tilde{x}_{ikl} \le \min\left(\frac{x_{ikl}}{a_{\emptyset kl}}, \tau_{kl}\right), \forall i\in I, k\in K, l\in L \tag{B.13}$$

$$x_{ikl}, z^S_{pw}, z^T_{mp}, z^A_q, z_{mpe}, z^V_m, z^O_{wr} \in \{0,1\} \tag{B.14}$$

$$y^S_{mpeq}, y^A_{iklq}, \tau_{kl}, \tilde{x}_{ikl} \ge 0. \tag{B.15}$$

References

Anderson, S. P., De Palma, A., & Thisse, J. F. (1992). *Discrete choice theory of product differentiation*. MIT Press.

Baumann, W. (2013). Bumper crops. *Car and Driver, 4*, 18–19.

Bazaraa, M. S., Sherali, H. D., & Shetty, C. M. (2013). *Nonlinear programming: Theory and algorithms*. John Wiley & Sons.

Brundtland, G., Khalid, M., Agnelli, S., Al-Athel, S., Chidzero, B., Fadika, L., et al. (1987). Report of the world commission on environment and development: Our common future ('Brundtland Report').

Chen, F., Eliashberg, J., & Zipkin, P. (1998). Customer preferences, supply-chain costs, and product-line design. In *Product variety management* (pp. 123–144). Springer.

Dawe, N. K., & Ryan, K. L. (2003). The faulty three-legged-stool model of sustainable development. *Conservation Biology, 17*(5), 1458–1460.

Denchak, M. (2016). Are the effects of global warming really that bad? NRDC. https://www.nrdc.org/stories/are-effects-global-warming-really-bad. Accessed: July 23rd, 2016.

Desai, P., Kekre, S., Radhakrishnan, S., & Srinivasan, K. (2001). Product differentiation and commonality in design: Balancing revenue and cost drivers. *Management Science, 47*(1), 37–51.

Dobson, G., & Kalish, S. (1993). Heuristics for pricing and positioning a product-line using conjoint and cost data. *Management Science, 39*(2), 160–175.

Ekins, P. (1999). European environmental taxes and charges: Recent experience, issues and trends. *Ecological Economics, 31*(1), 39–62.

Eliashberg, J., & Steinberg, R. (1993). Marketing-production joint decision-making. In J. Eliashberg, & J. D. Lilien (Eds.): *5, Handbooks in Operations Research and Management Science* (pp. 827–877). North Holland.

Geffen, C. A., & Rothenberg, S. (2000). Suppliers and environmental innovation: The automotive paint process. *International Journal of Operations & Production Management, 20*(2), 166–186.

Goldberg, P. K. (1998). The effects of the corporate average fuel efficiency standards in the U.S. *The Journal of Industrial Economics, 46*(1), 1–33.

Graedel, T., Allenby, B., & Comrie, P. (1995). Matrix approaches to abridged life cycle assessment. *Environmental Science & Technology, 29*(3), 134A–139A.

Green, P. E., & Srinivasan, V. (1978). Conjoint analysis in consumer research: Issues and outlook. *Journal of Consumer Research, 5*(2), 103–123.

Guadagni, P. M., & Little, J. D. (1983). A logit model of brand choice calibrated on scanner data. *Marketing Science, 2*(3), 203–238.

Heese, H. S., & Swaminathan, J. M. (2006). Product line design with component commonality and cost-reduction effort. *Manufacturing & Service Operations Management, 8*(2), 206–219.

Hendrickson, C., Horvath, A., Joshi, S., & Lave, L. (1998). Peer reviewed: Economic input–output models for environmental life-cycle assessment. *Environmental Science & Technology, 32*(7), 184A–191A.

Hoen, K., Tan, T., Fransoo, J., & Van Houtum, G. (2010). *Effect of carbon emission regulations on transport mode selection in supply chains*. Eindhoven University of Technology.

Honhon, D., Gaur, V., & Seshadri, S. (2010). Assortment planning and inventory decisions under stockout-based substitution. *Operations Research, 58*(5), 1364–1379.

Hotelling, H. (1929). Stability in competition. *The Economic Journal, 39*(153), 41–57.

IBM Ilog Cplex (2011). Optimization Studio. version 12.4, http://www.ilog.com/products/cplex.

Jones, P., Trenberth, K., Ambenje, P., Bojariu, R., Easterling, D., Klein, T., et al. (2007). Observations: Surface and atmospheric climate change. *Climate change* (pp. 235–336). IPCC.

Khan, Z. (2008). Cleaner production: An economical option for ISO certification in developing countries. *Journal of Cleaner Production, 16*(1), 22–27.

Kök, A. G., & Fisher, M. L. (2007). Demand estimation and assortment optimization under substitution: Methodology and application. *Operations Research, 55*(6), 1001–1021.

Kök, A. G., Fisher, M. L., & Vaidyanathan, R. (2008). Assortment planning: Review of literature and industry practice. In *Retail supply chain management* (pp. 99–153). Springer.

Koplin, J., Seuring, S., & Mesterharm, M. (2007). Incorporating sustainability into supply management in the automotive industry – the case of the Volkswagen AG. *Journal of Cleaner Production, 15*(11), 1053–1062.

Kremer, G. E., Haapala, K., Murat, A., Chinnam, R. B., Kim, K., Monplaisir, L., et al. (2016). Directions for instilling economic and environmental sustainability across product supply chains. *Journal of Cleaner Production, 112*, 2066–2078.

Lehle, H. (2016). *IHS global outlook for automotive sales*. United States Environmental Protection Agency (EPA). Accessed: July 23rd, 2016

Leontief, W. (1970). Environmental repercussions and the economic structure: an input-output approach. *The Review of Economics and Statistics, 52*(3), 262–271.

Ma, H., Balthasar, F., Tait, N., Riera-Palou, X., & Harrison, A. (2012). A new comparison between the life cycle greenhouse gas emissions of battery electric vehicles and internal combustion vehicles. *Energy Policy, 44*, 160–173.

MacDuffie, J. P., Sethuraman, K., & Fisher, M. L. (1996). Product variety and manufacturing performance: Evidence from the international automotive assembly plant study. *Management Science, 42*(3), 350–369.

MacLean, H. L., & Lave, L. B. (2000). Environmental implications of alternative-fueled automobiles: Air quality and greenhouse gas tradeoffs. *Environmental Science & Technology, 34*(2), 225–231.

Mahajan, S., & Van Ryzin, G. (2001). Stocking retail assortments under dynamic consumer substitution. *Operations Research, 49*(3), 334–351.

Michalek, J. J., Ceryan, O., Papalambros, P. Y., & Koren, Y. (2006). Balancing marketing and manufacturing objectives in product line design. *Journal of Mechanical Design, 128*(6), 1196–1204.

Michalek, J. J., Papalambros, P. Y., & Skerlos, S. J. (2004). A study of fuel efficiency and emission policy impact on optimal vehicle design decisions. *Journal of Mechanical Design, 126*(6), 1062–1070.

Moorthy, K. S. (1984). Market segmentation, self-selection, and product line design. *Marketing Science, 3*(4), 288–307.

Mussa, M., & Rosen, S. (1978). Monopoly and product quality. *Journal of Economic Theory, 18*(2), 301–317.

Nature.org (2016). Climate change: Threats and impacts, Nature.org. http://www.nature.org/ourinitiatives/urgentissues/global-warming-climate-change/threats-impacts/. Accessed: July 23rd, 2016.

Netessine, S., & Taylor, T. A. (2007). Product line design and production technology. *Marketing Science, 26*(1), 101–117.

Notter, D. A., Gauch, M., Widmer, R., Wager, P., Stamp, A., Zah, R., et al. (2010). Contribution of li-ion batteries to the environmental impact of electric vehicles. *Environmental Science & Technology, 44*(17), 6550–6556.

Padgett, J. P., Steinemann, A. C., Clarke, J. H., & Vandenbergh, M. P. (2008). A comparison of carbon calculators. *Environmental Impact Assessment Review, 28*(2), 106–115.

Pallaro, E., Subramanian, N., Abdulrahman, M. D., & Liu, C. (2015). Sustainable production and consumption in the automotive sector: Integrated review framework and research directions. *Sustainable Production and Consumption, 4*, 47–61.
Pil, F. K., & Holweg, M. (2004). Linking product variety to order-fulfillment strategies. *Interfaces, 34*(5), 394–403.
Rodríguez, B., & Aydın, G. (2011). Assortment selection and pricing for configurable products under demand uncertainty. *European Journal of Operational Research, 210*(3), 635–646.
Samaras, C., & Meisterling, K. (2008). Life cycle assessment of greenhouse gas emissions from plug-in hybrid vehicles: Implications for policy. *Environmental Science & Technology, 42*(9), 3170–3176.
Smith, S. A., & Agrawal, N. (2000). Management of multi-item retail inventory systems with demand substitution. *Operations Research, 48*(1), 50–64.
Spector, M. (2007). Can U.S. adopt Europe's fuel-efficient cars? *Wall Street Journal*. https://www.wsj.com/articles/SB118282251878547983. Accessed: September 5th, 2017.
Steenberghen, T., & Lopez, E. (2008). Overcoming barriers to the implementation of alternative fuels for road transport in Europe. *Journal of Cleaner Production, 16*(5), 577–590.
Sterner, T. (2007). Fuel taxes: An important instrument for climate policy. *Energy Policy, 35*(6), 3194–3202.
Taghavi, A., & Chinnam, R. B. (2014). Assortment planning of automotive products with considerations for economic and environmental impacts of technology selection. *Journal of Cleaner Production, 70*, 132–144.
Taylor, B. (2006). Encouraging industry to assess and implement cleaner production measures. *Journal of Cleaner Production, 14*(6), 601–609.
UCSUSA (2016). Cars, trucks, and air pollution: Transportation is the largest single source of air pollution in the United States. Union of Concerned Scientists UCSUSA. http://www.ucsusa.org/clean-vehicles/vehicles-air-pollution-and-human-health/cars-trucks-air-pollution#.V5FbUbiANBc. Accessed: July 23rd, 2016.
UCSUSA (2016). Global warming science: The science is clear. Global warming is happening. We are the primary cause. Union of Concerned Scientists UCSUSA. http://www.ucsusa.org/our-work/global-warming/science-and-impacts/global-warming-science#.V5FUNriANBc. Accessed: July 23rd, 2016.
Umpfenbach, E. L. (2013). *Optimization of strategic planning processes for configurable products: Considerations for marketing, supply chain, and sustainability*. Ph.D. thesis. Wayne State University.
United Nations (2016). U.N. sustainable development goals: 17 goals to transform our world, Goal 13: Take urgent action to combat climate change and its impacts, http://www.un.org/sustainabledevelopment/climate-change-2/. Accessed: July 23rd, 2016.
U.S. Department of State (2014). U.S. climate action report. http://www.state.gov/documents/organization/219038.pdf. Accessed: July 23rd, 2016.
U.S. EPA (2014). Global greenhouse gas emissions data. United States Environmental Protection Agency (EPA). https://www3.epa.gov/climatechange/ghgemissions/global.html. Accessed: July 23rd, 2016.
U.S. EPA (2014). U.S. carbon dioxide emissions by source between 1990–2014. United States Environmental Protection Agency (EPA). https://www3.epa.gov/climatechange/ghgemissions/gases/co2.html. Accessed: July 23rd, 2016.
Van Ryzin, G., & Mahajan, S. (1999). On the relationship between inventory costs and variety benefits in retail assortments. *Management Science, 45*(11), 1496–1509.
Wesoff, E. (2016). How soon can Tesla get battery cell costs below $100 per kilowatt-hour? http://www.greentechmedia.com/articles/read/How-Soon-Can-Tesla-Get-Battery-Cell-Cost-Below-100-per-Kilowatt-Hour#disqus_thread. Accessed: July 23rd, 2016.
Williamson, R., & Beasley, J. (2011). Automotive technology and manufacturing readiness levels: A guide to recognised stages of development within the automotive industry. *Low Carbon Vehicle Partnership* (pp. 1–7). Automotive Council.
Wilson, A. (2008). Ford reins in F-150 order combinations. *Automotive News*, 4 http://www.autonews.com/article/20080819/ZZZ_SPECIAL/113735/ford-reins-in-f-150-order-combinations. Accessed: September 5th, 2017.
Womack, J. P., Jones, D. T., & Roos, D. (1990). *Machine that changed the world*. Simon and Schuster.